Electrocardiogram profiling of myocardial infarction history using MLP and HMLP networks

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Article Info

ABSTRACT

Narrowing of coronary arteries caused by cholesterol deposits deprives heart tissues of oxygen. In prolonged conditions, these will result in myocardium infarction. The presence of damage tissues modifies the normal sinus rhythm and this can be detected using electrocardiogram (ECG). Hence, this paper characterized history of myocardial infarction from survivors using QRS power ratio features from the ECG. Subsequent profiling is performed using multilayered perceptron (MLP) and hybrid multilayered perceptron (HMLP) networks. ECG with history of anterior and inferior infarctions, along with healthy controls is obtained from PTB Diagnostic ECG Database. The signal is initially pre-processed and the power ratio features are extracted for low- and mid-frequency components. The features are then used as input vector to the MLP and HMLP networks. The optimized MLP has attained accuracies of 99.2% for training and 98.0% for testing. Meanwhile, the optimized HMLP managed to achieve accuracies of 99.4% for training and 97.8% for testing. Despite the similarities in network performance, MLP provides a better alternative due to the reduced computational requirements by as much as 30%.

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1. INTRODUCTION

Acute myocardial infarction is caused by prolonged ischemic conditions which often result in necrosis of myocardium tissues. Delay in delivery of treatment will lead to cardiac arrest and in most cases, death [1-2]. Previously, studies have established ECG pattern for patients who survived myocardial infarction. These were initially grounded on the notion that impaired heart tissues will induce abnormalities to the healthy sinus rhythm [3-4]. These can be detected through the ECG; a non-invasive technique for recording electrical activities of the heart. Such approach is made possible through the use of specialized silver-chloride electrodes that are connected to the limbs; effectively forming the leads that represent the frontal plane of the heart [5]. The lead orientations enable detection of abnormalities within the electrical conduction system; hence allowing a more targeted and precise treatment [6]. Apart from myocardial infarction, previously studied arrhythmias are cardiomyopathy [7-8], premature ventricular contractions [9-10], and bundle branch blocks [11-12].

Past studies involving profiling of myocardial infarction history have implemented the ECG power ratio features from both of the frontal limb leads. These were based on three pre-defined frequency components of the QRS-complex. The results however, indicate that only the low-frequency (5-15Hz) and mid-frequency (15-50Hz) zones are capable of discriminating healthy control from ECG with history of

anterior and inferior infarctions with acceptable accuracies. A comparative analysis have also highlighted that the information from both bipolar and unipolar limb leads yielded similar performance [13]. Therefore, either one of the lead system would suffice for the development of more advanced profile model.

Previously, history profiling has been performed using MLP network. The intelligent model yielded satisfactory performance using the low- and mid-frequency QRS power ratio features [13]. MLP is advantageous as it is able at learning complex non-linear relationships and generalizes solution for a given problem [14-15]. In the past, the ECG profiling model was optimized using modified constructive algorithm which assesses optimum number of hidden nodes based on best average accuracies and mean squared error (MSE) [16]. The methods for setting the upper and lower boundary conditions are flawed as it is derived from limited assumptions. Often, a better alternative in terms of number of hidden nodes is attained by selecting values beyond the range of conventional boundary conditions [10].

Similar optimization issues are also present for HMLP network. The hybrid structure is an improvement of MLP; with parallel weighted connection directly from input and the output node. Studies have shown that the network is capable of modelling linear and non-linear relationships with better accuracies compared to the conventional MLP. For function approximation problems however, it has shown to consume more time for network training [17-18]. To date, HMLP has yet to be implemented to profile ECG with myocardial infarction history.

Hence, three objectives have been outlined in this study; 1) to characterize QRS power ratio features for healthy control, as well as ECG with history of anterior and inferior myocardial infarction, 2) to develop ECG profile models using MLP and HMLP network, and 3) to evaluate the best network model based on classification performance and computational requirements.

2. RESEARCH METHOD

The initial part of the study encompasses data acquisition, signal pre-processing, as well as extraction of low- (LF-QRS) and med-frequency (MF-QRS) power ratio features. Subjects are then segregated into classes of anterior and inferior infarction histories, as well as healthy controls. Subsequently, the structure of MLP and HMLP network is optimized using modified constructive algorithm. The best number of hidden nodes is implemented in the development of ECG profile models using both MLP and HMLP. Finally, performance of both network structures are analyzed in terms of accuracy and computational requirements.

2.1. Data Collection and Signal Pre-Processing

Comprehensive data with infarction histories, along with the healthy controls is acquired from the PTB Diagnostic ECG database. ECG has been recorded at sampling rate of 1 kHz using the Physikalisch-Technische Bundesanstalt prototype device [19]. In this study, only bipolar limb lead is selected. Table 1 shows the number of subjects for each ECG class and its corresponding indexes.

Table 1. Number of Subjects for the Respective ECG Class

ECG Class	Number of Subjects	Index
Anterior infarction	27	1
Inferior infarction	36	2
Healthy control	24	3

2.2. Extraction of QRS Power Ratio Features

ECG is filtered into LF-QRS and MF-QRS components using finite impulse response band-pass filters [20]. The ECG is segregated into smaller segments of five second sample. Hence, the total number of samples obtained is 1206 each class. Each sample is transformed to power spectral density (PSD). The procedure is performed using Welch technique. Subsequently, the area under PSD curve is quantified as energy spectral density (ESD). The ESD is then normalized using (1), (2) and (3), where I, II and III each refers to information from Lead I, II and III [13]. The power ratio, computed for both frequency components are then clustered into the respective ECG classes for pattern analysis. These are performed using box plots in SPSS.

$$\text{Power Ratio I} = \frac{\text{ESD}_I}{\text{ESD}_I + \text{ESD}_{II} + \text{ESD}_{III}}$$

(1)

$$\text{Power Ratio II} = \frac{\text{ESD}_{II}}{\text{ESD}_I + \text{ESD}_{II} + \text{ESD}_{III}}$$

(2)

$$\text{Power Ratio III} = \frac{\text{ESD}_{III}}{\text{ESD}_I + \text{ESD}_{II} + \text{ESD}_{III}}$$

(3)

2.3. Multilayered Perceptron Network

Generally, the MLP is composed of an input layer, several hidden layers and an output layer. Studies have shown that single hidden layer is sufficient for function approximation with acceptable level of accuracies. The number of input nodes depends on the size of feature vector. Therefore in this study, the network is fed by six inputs. Conversely, only one output node which corresponds to the ECG indexes is implemented. As expressed by (4), feature input, x_i is converted to vector of hidden variables, u_j via activation function, $\Gamma 1$. M is the number of input nodes, w_{ij} is the weights between ith input to jth hidden node, and θ_j are the biases. $\Gamma 1$ adopts hyperbolic tangent function [21-22].

$$u_j = \Gamma_1 \left(\sum_{i=1}^{M} w_{ij} x_i + \theta_j \right)$$

(4)

Consequently, vector u_j is transformed into the resultant output, y_k, via activation function $\Gamma 2$. This can be expressed by (5), where N is the number of hidden nodes, w_{jk} is the weights between jth hidden node to kth output node, and θ_k are the biases. $\Gamma 2$ adopts the pure linear function to approximate the corresponding class indexes [21-22].

$$y_k = \Gamma_2 \left(\sum_{j=1}^{N} w_{jk} u_j + \theta_k \right)$$

(5)

The error, computed as the difference between y_k and the desired output is integrated into the Levenberg-Marquardt algorithm for network training [23-24]. Convergence of error is monitored via MSE. In this study, early-stopping criterion is implemented to avoid network from over-fitting. A separate validation data is used to intermittently evaluate the network for its generalization ability. Training is halted when validation error increases. Testing set is used to assess performance of the fully trained network. The dataset is randomly segregated for training, validation and testing with a ratio of 70:15:15.

The best number of hidden nodes is evaluated using modified constructive algorithm. For every hidden node configuration, the network is trained forty times. At each training cycle, the network will reset at randomized starting weights and biases. Hence, an optimum number of hidden nodes will induce the best average performance, irrespective of pseudorandom Mersenne twister settings. The method determines the most suitable number of hidden nodes through the highest average accuracy and lowest average MSE during training. In this study, the number of hidden nodes ranges from five to twenty.

2.4. Hybrid Multilayered Perceptron Network

HMLP is a modification of MLP architecture with additional connections from input to the output layer. With this structure, y_k no longer rely only on vector u_j, but also considers vector x_i. This can be mathematically expressed by (6) [25-26].

$$y_k = \Gamma_2 \left(\sum_{j=1}^{N} w_{jk} u_j + \theta_k + \sum_{i=1}^{M} w_{ik} x_i \right)$$

(6)

Due to the presence of linear component, the complexity of computational requirements increases by an additional six multiplier and adder operations. This will be reflected in longer processing time. Despite the limitations, HMLP has been widely implemented to model non-linear relationships and has shown to exhibit superior performance than the preceding MLP. In this study, development of ECG profile models using HMLP adopts similar configurations as MLP in terms of optimization method, activation functions, learning algorithm, early-stopping criterion, and dataset segregation for training, validation and testing.

2.5. Performance Metrics

The parameters used to evaluate model performance are accuracy (Acc), sensitivity (Se) and positive predictivity (Pp). Each is expressed by (7), (8) and (9). TP is the true positive, TN is the true negative, FP is the false positive, and FN is the false negative classifications.

$$Acc = \left(\frac{TP + TN}{TP + TN + FP + FN} \right) \times 100\%$$

(7)

$$Se = \left(\frac{TP}{TP + FP} \right) \times 100\%$$

(8)

$$Pp = \left(\frac{TP}{TP + FN} \right) \times 100\%$$

(9)

3. RESULTS AND DISCUSSION

Initially, the discussion elaborates on the characteristics of QRS power ratio features for ECG with infarction histories, along with the healthy controls. This is followed by optimization and development of ECG profile model using MLP network. Subsequently, similar scope of discussion ensues for ECG profile model via HMLP network. Performance of both methods is compared based on overall accuracy and computational requirements.

3.1. Characterization of QRS Power Ratio Features for Different ECG Profiles

The pattern of mean and distribution of LF-QRS power ratio for the three control groups is shown in Figure 1. Healthy control exhibit the lowest mean for Lead I, followed by those with anterior and then, inferior infarctions. Meanwhile for Lead II, the lowest median is attained by subjects with damage to inferior, followed by anterior aspects of the heart. It is worth noting that the median for both groups is almost similar. Conversely, the lowest median for Lead III has been attained by healthy controls, followed by subjects who survived anterior and subsequently, inferior infarctions. No extreme outliers have been observed.
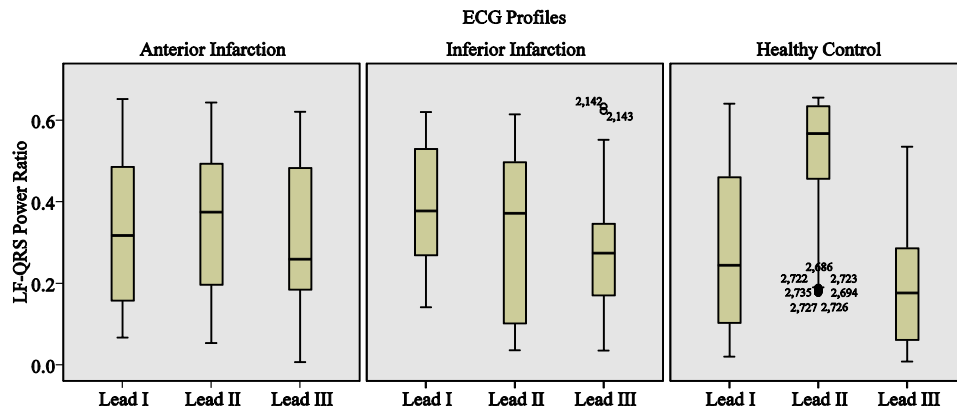

Figure 1. Pattern and distribution of LF-QRS power ratio for different ECG profiles

Consequently, Figure 2 shows the pattern of median and distribution of MF-QRS power ratio for the three control groups. The lowest median for Lead I is attained by healthy controls, followed by subjects who suffered from anterior and then, inferior infarctions. Meanwhile for Lead II, the lowest median is yielded by those with damage to anterior, followed by inferior positions. Healthy controls have attained the highest median for Lead II. Conversely, the lowest median for Lead III is obtained by healthy controls, followed by subjects with inferior and subsequently, anterior infarctions. No extreme outlier has been observed for MF-QRS power ratio features.
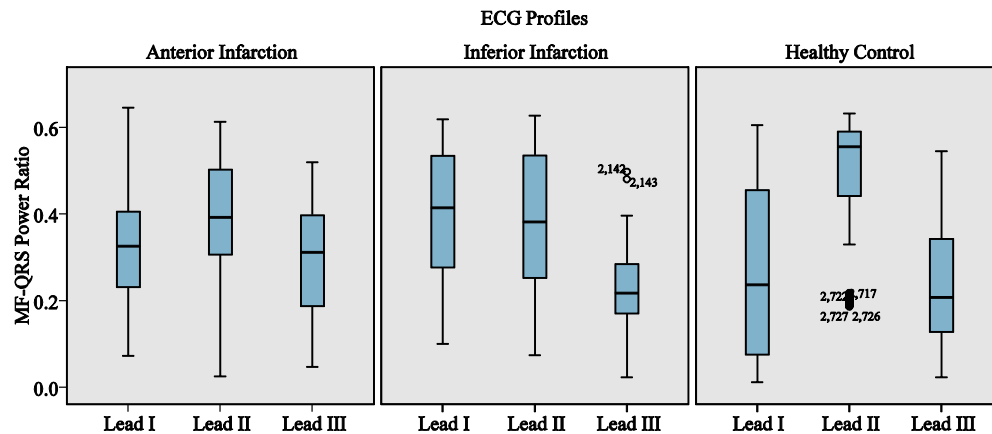
Figure 2. Pattern and distribution of MF-QRS power ratio for different ECG profiles

3.2. Development of ECG Profile Model Using Multilayered Perceptron Network

The average training accuracies and MSE for different hidden node configurations in MLP is shown in Figure 3. The average accuracies increase from 63.2% for five hidden nodes, to 99.3% for twenty hidden nodes. Meanwhile, the trend of MSE indicates a reciprocal relationship with the preceding results. The average MSE decreases from 0.23 for five hidden nodes, to 0.02 for twenty hidden nodes. To maintain balance between excellent model performance and increasingly complex computatinal requirement, the optimum number of hidden nodes is selected at thirteen with approximate accuracy of 95.0% and MSE of 0.05 for training.
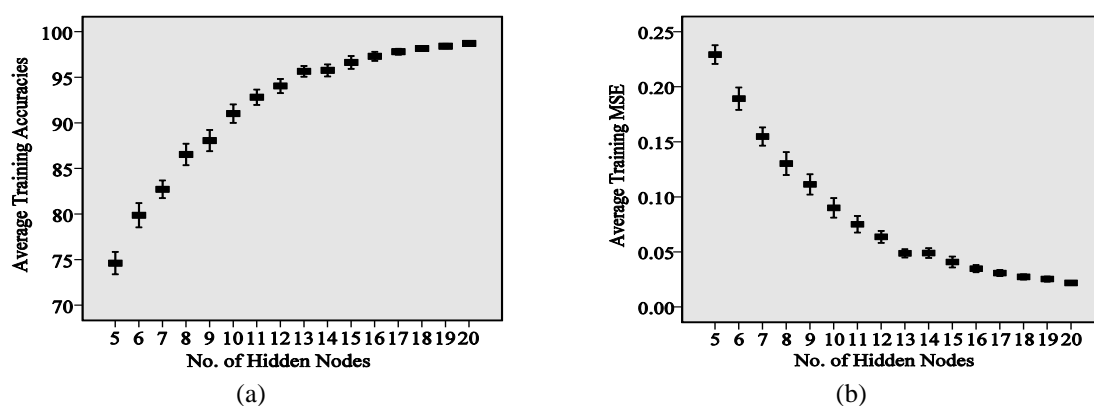

| (a) | (b) |

Figure 3. Average training (a) accuracies and (b) MSE analysis for MLP network

The ECG profile model is then developed with the optimized network structure. As shown in Table 2, excellent performance has been achieved with accuracies of 98.0% for training, 97.3% for validation and 99.2% for testing. Sensitivity and positive predictivity measures further indicate that despite the high degree of feature overlapping, the model is able to discriminate between control groups with exceptional accuracies.

Table 2. Model Performance using MLP Network

Parameters		Anterior Infarction	Inferior Infarction	Healthy Controls	*Acc*
Training	*Se*	98.4%	97.5%	96.2%	98.0%
	Pp	98.3%	96.9%	98.9%	
Validation	*Se*	97.8%	98.1%	96.0%	97.3%
	Pp	98.9%	93.5%	99.4%	
Testing	*Se*	99.4%	98.8%	99.4%	99.2%
	Pp	100%	98.8%	98.9%	

3.3. Development of ECG Profile Model Using Hybrid Multilayered Perceptron Network

For HMLP network, the average training accuracies and MSE for different hidden node configurations is shown in Figure 4. The average accuracies increase from 70.4% for five hidden nodes, to 99.5% for twenty hidden nodes. At five hidden nodes, HMLP has already surpassed the performance of MLP network. The average training MSE for varying number of hidden nodes in HMLP is shown Figure 4. The pattern indicates a reciprocal relationship with the prior results. The average MSE decreases from 0.21 for five hidden nodes, to 0.02 for twenty hidden nodes. Similar to MLP, the optimum number of hidden nodes is selected at thirteen with approximate accuracy of 95.0% and MSE of 0.05 for training.

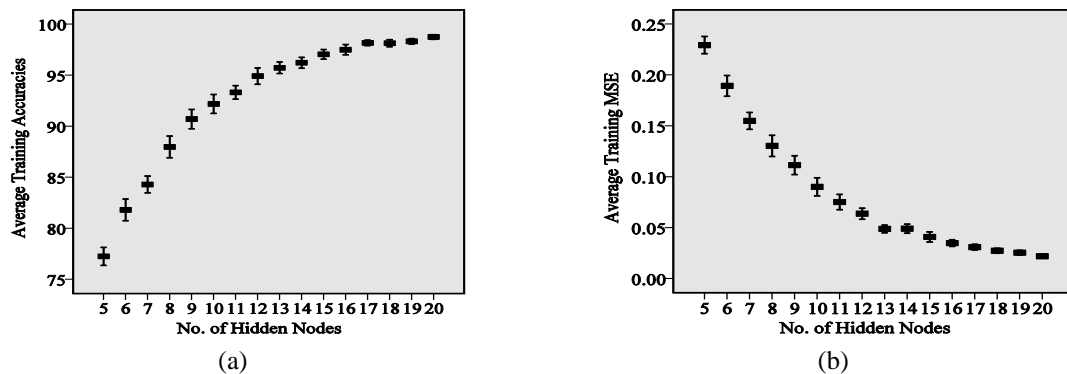|	
(a)	(b)

Figure 4. Average training (a) accuracies and (b) MSE analysis for HMLP network

The ECG profile model is then developed with the optimized network structure. As shown in Table 3, excellent performance has been attained with accuracies of 97.9% for training, 98.5% for validation and 99.4% for testing. Similarly with MLP, the model is still able to discriminate between subjects who survived anterior and inferior infarctions, as well as healthy controls with exceptional accuracies.

Table 3. Model Performance using HMLP Network

Parameters		Anterior Infarction	Inferior Infarction	Healthy Controls	*Acc*
Training	*Se*	99.1%	96.3%	98.5%	97.9%
	Pp	98.5%	97.6%	97.7%	
Validation	*Se*	98.9%	97.5%	98.8%	98.5%
	Pp	99.5%	97.5%	98.2%	
Testing	*Se*	100%	99.5%	98.8%	99.4%
	Pp	100%	99.0%	99.4%	

3.4. Performance Comparison

Thus far, ECG profile models have been successfully developed from QRS power ratio features using MLP and HMLP. Despite the structural differences, both networks are optimized at thirteen hidden nodes. Table 4 compares the number of multiplier and adder operators required for the proposed methods.

Table 4. Number of Operators for MLP and HMLP Networks

Network	Layer	Multiplier	Adder
MLP	u_j	91	78
	y_k	14	13
HMLP	u_j	91	78
	y_k	20	19

The number of operators remains unchanged at hidden layer. However, the effects of additional connection can be observed for the output node. Hence for forward propagating computation, the load for multiplier and adder operations increases by 42.9% and 46.2%, respectively. Meanwhile, similarities have also been observed in terms of classification accuracies. Thus, MLP is recommended over HMLP as it is able to provide optimum performance, even in the absence of additional input-output connection.

4. CONCLUSION

This paper presents an ECG profiling of myocardial infarction history using MLP and HMLP network. The three outlined objectives earlier have successfully been solved. Initially, ECG with infarction survivors and healthy controls are characterized using QRS power ratio features from bipolar limb leads. Subsequently, the proposed MLP and HMLP network structures have been optimized as ECG profile models with excellent classification accuracies. Despite the similarities in terms of performance, analysis shows that MLP is comparatively more efficient than HMLP as it reduces computational requirements by up to 30%.

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